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Research Article

A Novel Approach Based on Generative Adversarial Network for Signal Enhancement in Wireless Communications

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Wireless communication signals are often affected by noise and interference in the channel during transmission, which makes it difficult for the receiver to analyze. The signal enhancement technology can suppress the noise and interference in the signal, so as to improve the communication quality. It is one of the main research directions of signal processing. Classical enhancement methods separate the signals through separable transform domain. Artificial construction of the corresponding separable transform domain requires prior information of noise and interference, but they have the characteristics of randomness. Further, these methods usually use high-level features and rely on statistics, so they can only deal with specific noise conditions. At present, deep learning is increasingly applied in the field of wireless communications due to its powerful feature extraction ability for large sample sets. In this paper, a communication signal enhancement model based on generative adversarial network (GAN) is proposed. Compared with classical methods, the signal is operated directly and the model is trained end-to-end. It can adapt to different noise conditions and avoid the above problems. An independent and invisible test set is used to evaluate several comparative methods. The experimental results confirm the effectiveness of the proposed model.

1. Introduction

Cognitive radio technology has shown superior performance in the field of wireless communications [1]. In the transmission process, however, the signal cannot avoid the influence of noise and interference due to the limited transmission bandwidth and the multipath effect of the channel. It increases the difficulty of demodulation and reduces the ability of spectrum sensing. Since it is meaningful to process and analyze high-quality signals, it is necessary to eliminate noise and interference in the received signals. Signal enhancement attempts to improve the signal quality in noisy environments, which can promote the development of communication technology. In addition, it can also be used in the preprocessing stage of wireless communications.

A variety of signal enhancement methods have been proposed, mainly divided into two categories: linear method and nonlinear method [2]. Based on the assumption that the signal is stationary, the linear method is relatively simple, but it may not find the global optimal solution to eliminate noise and interference. The actual communication signal usually has nonstationary statistical characteristics, so the nonlinear method has more advantages, which uses the time and spectrum information in the signal. Traditional methods need prior information of noise and interference, and then map them into separable transform domain for separation. However, the randomness of noise and interference makes it difficult to construct the corresponding separable transform domain. So these methods fail to adaptively complete real-time signal enhancement.

In terms of frequency domain, nonstationary interference can be eliminated by using band-pass filters, then the signal in the required frequency band can be obtained. In the ideal case, once the corresponding index is given, the filter can be designed to meet the requirements [3]. But in the general case, the parameters of the signal to be identified may be unknown, such as bandwidth and center frequency. And the influence of the external environment on the statistical characteristics of the received signal is unpredictable. These make the performance of the predesigned filter degrade, or even fail to work. Consequently, adaptive filters are proposed to solve these problems [4]. Their optimization process is adjusted according to the changes of the external environment. Since the response is relatively lagging, it is difficult for them to deal with the interference signal whose statistical characteristics change rapidly. In brief, classical enhancement methods use filters or transform domains to eliminate noise and interference, and they cannot adaptively learn signal features.

In recent years, deep learning has been used to solve many classical communication problems. Compared with machine learning algorithm, the deep learning model has better ability of feature extraction and adaptive learning for complex and dynamic data distribution. It has made great progress in the field of wireless communications [5, 6]. These valuable researches provide some references for communication signal enhancement. For the method based on deep learning, there is no need to make clear assumptions about the original data, and its application in electromagnetic signal anti-interference, which means the reduction and suppression of interference existing in the signal will become a development trend [7–9].

Generative model is a learning framework [10], whose purpose is to generate fake samples like real ones. An important breakthrough of deep learning in generative model is generative adversarial network (GAN) [11]. GAN has shown excellent performance in the field of computer vision. It can generate realistic images and learn complex high-dimensional distributions. For wireless communications, it is also applied to spectrum sensing tasks [12].

Inspired by SEGAN [13], a communication signal enhancement model based on generative adversarial network is constructed in this paper. The model avoids complex transformation of the original signal. And its end-to-end structure is different from the traditional method. It adaptively eliminates dynamic noise and interference, thus has better robustness. The generator in the model learns the distribution characteristics of the original signal in an adversarial way. And the original signal is used as conditional information to generate an enhanced signal. Even if the external environment changes, the model can effectively achieve the goal of signal enhancement. The training process is independent of the specific application, so it can be embedded into the wireless communication system as a preprocessing module.

The proposed communication signal enhancement model is universal and real-time. Its main advantages include: (1) it adopts an end-to-end mode and operates signals directly. The model avoids extracting artificial features through intermediate transformation and making clear assumptions on the original data, which is quite different from the common pipeline. (2) It provides a fast enhancement process. The model excludes causality and recursive operations like recurrent neural network (RNN) [14]. (3) It learns from different types of signals and interferences. The model has good adaptive ability. Although the statistical characteristics of the external environment are variable and unpredictable, the performance of the model is not affected.

The specific contents of this paper are summarized as follows: next, the principle and structure of generative adversarial network are introduced. In Section 3, the proposed model is described in detail. The parameter settings are described and the experimental results are discussed in Section 4. Finally, this paper is concluded in Section 5.

2. Generative Adversarial Network

GAN is a generative model, which generates new samples according to the real data distribution through adversarial training. It consists of two components: a generator G and a discriminator D. The task of G is to learn an effective mapping that simulates the real data distribution and generates new samples. G learns by mapping the distribution characteristics to a predefined manifold, rather than by memorizing input-output pairs. D is a typical binary classifier. Its purpose is to classify the samples from the original data as real and the samples generated by G as fake.

The adversarial behavior is that G generates fake samples, while D distinguishes between real samples from original data and fake samples generated by G. G tries to trick D into classifying the fake samples as real. In the process of back propagation, D gets better in finding the real distribution characteristics. In turn, G adjusts its parameters to make the fake samples closer to the real data manifold. Through alternate training, G and D form a dynamic game process, as shown in Figure 1. According to the feedback of D, G gradually generates fake samples similar to real samples. When the training balance is reached, D can only randomly discriminate whether the samples generated by G are real or fake. It means that the discrimination accuracy of D is about 50 percent. The objective function of GAN is expressed in the following as a min-max game between G and D:

$$\min_G \max_D V(D, G) = E_{x\sim p_X(x)}[\log D(x)] + E_{z\sim p_Z(z)}[\log (1 - D(G(z)))]. \tag{1}$$

3. Communication Signal Enhancement Model

3.1. Objective Function. The original GAN is difficult to control with the generated samples, which leads to the mismatch between the enhanced signal and the noisy signal. In order to solve this problem, conditional generative adversarial network (CGAN) is introduced in this paper. In CGAN, conditional variables guide the data generation process [15]. The additional information helps G and D perform mapping and classification. In this way, the model is ensured to generate a corresponding enhanced signal. In the proposed model, the clean signal is used as a conditional variable, and the objective function is changed to the following:

$$\begin{aligned}\min_G \max_D V(D, G) = {} & E_{x,x_c\sim p_X(x,x_c)}[\log D(x, x_c)] \\ & + E_{z\sim p_Z(z),x_c\sim p_X(x_c)}[\log (1 - D(G(z, x_c), x_c))].\end{aligned} \tag{2}$$

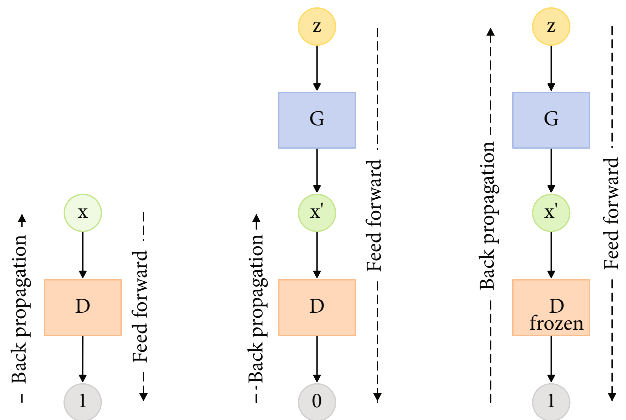

FIGURE 1: Dynamic game of GAN.

The classical GAN suffers from gradient disappearance due to the cross entropy loss used for training. In view of this problem, least square generative adversarial network (LSGAN) uses the least square function to replace the sigmoid cross entropy [16]. This improvement can stabilize the training and improve the quality of the generated samples. The proposed model adopts a binary form of the least square function, where 1 and 0 represent real and fake, respectively. Therefore, the above equation is changed to the following form:

$$\min_D V(D) = E_{x,x_c\sim p_X(x,x_c)}\left[(D(x,x_c)-1)^2\right] + E_{z\sim p_Z(z),x_c\sim p_X(x_c)}\left[D(G(z,x_c),x_c)^2\right], \tag{3}$$

$$\min_G V(G) = E_{z\sim p_Z(z),x_c\sim p_X(x_c)}\left[(D(G(z,x_c),x_c)-1)^2\right]. \tag{4}$$

In order to minimize the distance between the generated sample and the original sample, a minor component should be added to the loss of generator G. In the proposed model, L_1 norm is selected to represent the distance, which has been proved to be effective in the field of image processing [17]. In this way, G can generate more fine-grained samples and approximate the original signal waveform. The magnitude of L_1 norm is controlled by hyperparameter α, and the loss function of G is further changed to:

$$\min_G V(G) = E_{z\sim p_Z(z),x_c\sim p_X(x_c)}\left[(D(G(z,x_c),x_c)-1)^2\right] + \alpha\|G(z,x_c)-x\|_1. \tag{5}$$

3.2. Generator Structure. The structure of generator G is similar to that of auto-encoder [18], as shown in Figure 2. In the encoding stage, the input signal is compressed through multiplestrided convolutional layers, followed by Leaky ReLU. For the training of GAN, strided convolution is proved to be more stable than other pooling methods [19], so it is selected to calculate the convolution results. Compression is performed until the representation vector c is obtained, which is connected to the latent vector z. The encoding process is reversed by deconvolution in the decoding stage, also followed by Leaky ReLU.

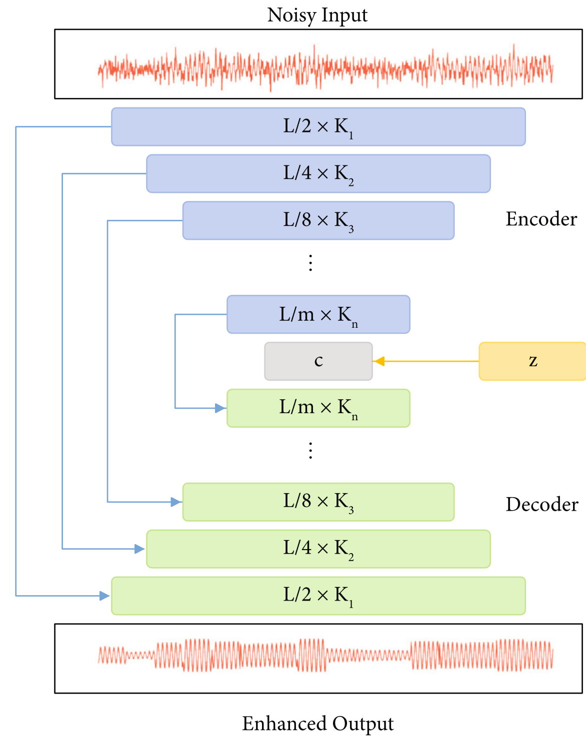

FIGURE 2: Structure of G.

The structure of generator G also includes skip connections, as shown in Figure 2. They connect each encoding layer to its corresponding decoding layer and bypass the compression performed in the middle of the structure. In this way, the inputs and outputs of the network share the same features. On the contrary, if all the information is forced through the compression, many low-level details used to accurately reconstruct the signal may be lost. The skip connections directly transfer the fine-grained information of the signal to the decoding stage. In addition, they can provide better training behavior, because gradients can pass deeper through the entire structure [20].

3.3. Convolutional Layer. Both generator G and discriminator D are composed of convolutional layers, without fully connected layers. It makes the model focus on the correlation in the input signal. In addition, it reduces the training parameters, thus reduces the training time.

The encoding-decoding structure of G is composed of strided convolutional layers and corresponding deconvolutional layers. In the encoding stage, the number of filters in each layer increases compared with the previous layer. Therefore, the depth gets larger as the width gets smaller. As described above, the decoding stage is symmetrical to the encoding stage, with the same number and size of filters per layer. Skip connections and additional latent vectors double the number of feature maps in each layer. Finally, the generated signal can be restored to the same width as the input signal.

D follows almost the same convolution structure as the encoding stage of G. The difference is that it has dual input channels and an extra convolutional layer for classification.

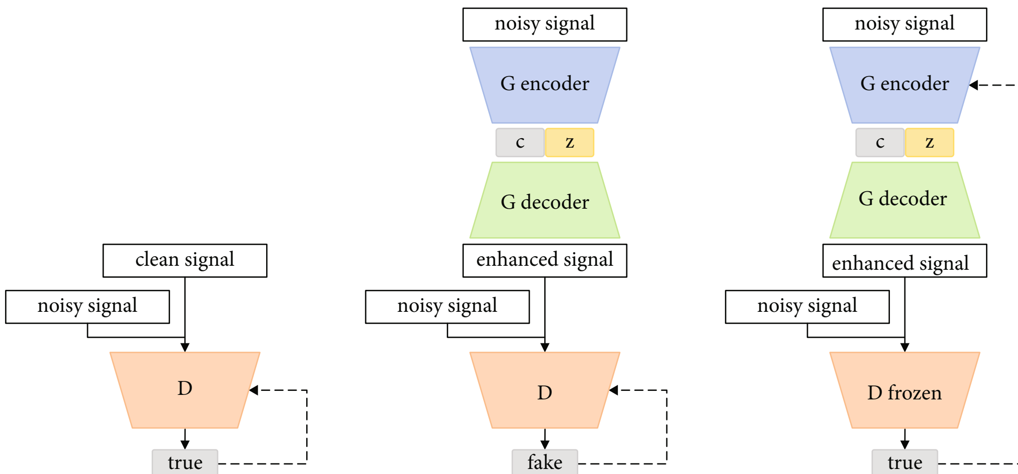

Figure 3: Adversarial training of the proposed model.

The extra convolutional layer is connected after the last activation layer, in which the filter width is 1. It further reduces the number of parameters required for classification.

In the proposed model, virtual batch normalization (VBN) is performed after the convolutional layer, which normalizes the input of each neuron and adds a bias term [21]. VBN can not only solve the problem of unstable training caused by poor initialization but also avoid the problem in which generator G maps the generated samples to a single point.

For the problem of communication signal enhancement, the noisy signal is processed to obtain an enhanced signal. Based on generative adversarial network, a communication signal enhancement model is proposed in this paper. The adversarial training of the proposed model is shown in Figure 3, which can be regarded as a game process between G and D. The generator G performs enhancement, its input is a noisy signal and a latent representation, and its output is an enhanced signal. The discriminator D performs classification, its input is a real pair composed of a noisy signal and a clean signal, or a fake pair composed of a noisy signal and an enhanced signal. According to the characteristics of communication signals, the conditional generative adversarial network is adopted, the loss function is improved, and the model structure is established. On this basis, the proposed model can eliminate the noise and interference in the signal without extracting artificial features.

4. Evaluation

4.1. Parameter Setup. In order to verify the validity of the proposed model, a simulated communication dataset is used in this paper. For signal types, several modulation modes with wide application and high spectral efficiency are selected in the experiment, including BPSK, QPSK, 8PSK, 16QAM, and 32QAM. There are two sets of signals: the original clean signal and the noisy signal with noise and interference. The noisy signal to be enhanced is composed of clean signal, Gaussian white noise, and other interference signals. In the training phase, the clean signal and the corresponding noisy signal are connected then fed to the model, where the clean signal is used as a condition. In order to further prove the adaptability of the proposed model, the test set is set to be different from the training set, the noise and interference in the test set are also set to be different from those in the training set.

In the experiment, the signal is down-sampled at a sampling rate of 2 MHz, and a sliding window is used to segment the signal into a fixed length of 1024 sampling points. The total number of signals in the training set and the test set for each condition is 9000 and 1000, respectively. Adam optimizer is adopted to optimize network parameters. The learning rate is set to 0.0002, the epoch is set to 20, and the batch size is set to 100. For the network structure, the generator G is composed of 14 convolutional layers, with a filter width of 31 and a stride of 2. All hyperparameters are determined by a large number of experiments.

4.2. Experimental Results. In order to evaluate the quality of the enhanced signal, signal-to-noise ratio (SNR) and root mean square error (RMSE) are selected as evaluation metrics in the experiment. Three typical enhancement systems based on deep learning are constructed as the baseline method, which further demonstrates the superiority of the proposed model. The first one uses deep auto-encoder (DAE) [22], which is a network structure commonly used for denoising. The second one uses convolutional neural network (CNN) for enhancement [23]. The third one is a modification of GAN [24].

The goal of alternate training is to get a generative network, which removes noise and interference, then realizes signal enhancement. After the training is completed, the noisy signal is fed into the generative network to obtain an enhanced signal. Figures 4–6 show the clean signal, the noisy signal, and the enhanced signal generated by the proposed model, respectively, when the modulation mode is 16QAM and the SNR is 0 dB. The signals before and after enhancement are compared in terms of waveforms. It can be seen that the enhanced signal is similar to the original clean signal.

In the first part of the experiment, a specific modulation signal is optimized, which is only overlapped by noise. The

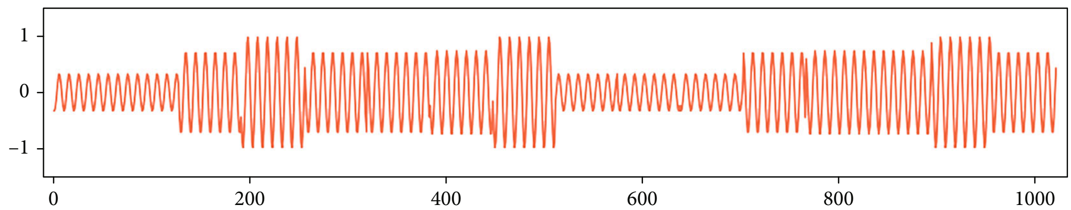

Figure 4: Clean signal.

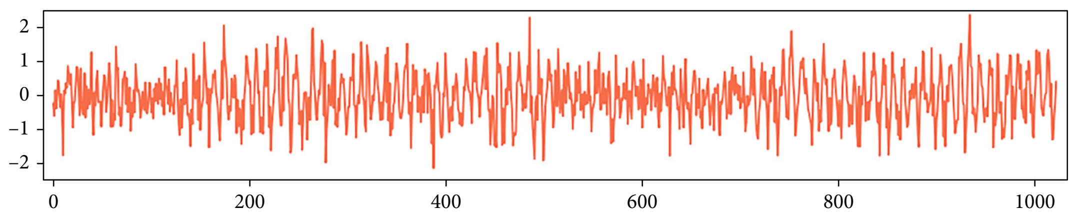

Figure 5: Noisy signal.

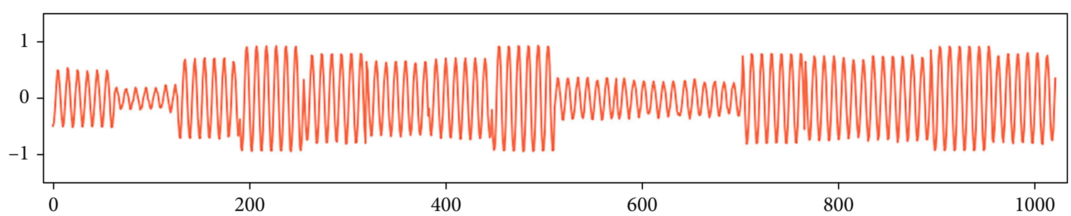

Figure 6: Enhanced signal generated by the proposed model.

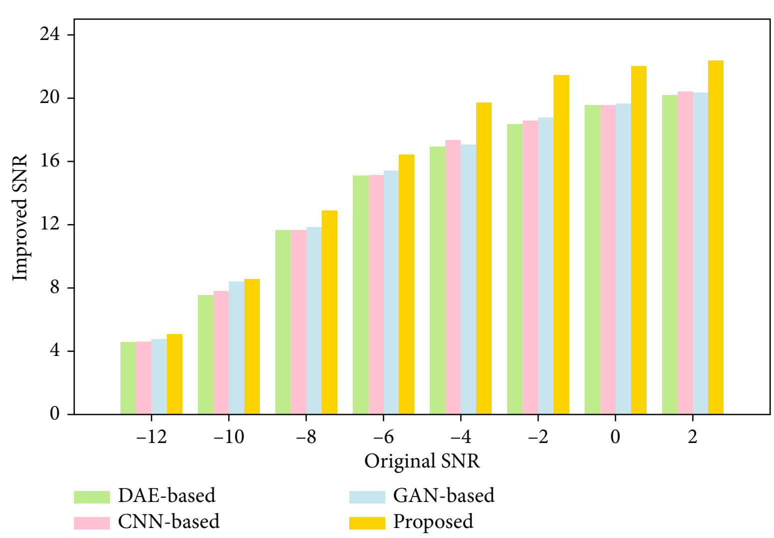

Figure 7: Improvement of SNR in QPSK scene.

improved SNR is calculated, the higher the better. In order to intuitively reflect the enhancement effect in QPSK scene, Figure 7 depicts the improvement comparison of four methods for noisy signals with different original SNR. As can be seen, all methods can solve the problem of signal enhancement, and the proposed model performs better. Whether in the case of high or low SNR, it provides better results than other methods.

The enhancement model should not be limited to certain types of wireless signals, but should be suitable for most types. Therefore, a signal dataset composed of other modulation modes is also tested, in which the original signal is

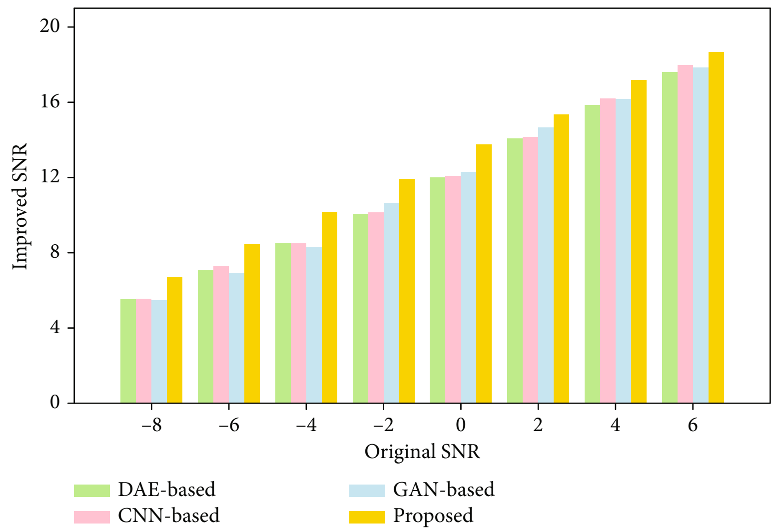

Figure 8: Improvement of SNR in 16QAM scene.

Table 1: RMSE for specific SNR in 16QAM scene.

Methods	-8	-6	-4	-2	0	2	4	6
DAE-based	0.2940	0.2467	0.2068	0.1721	0.1412	0.1164	0.0938	0.0815
CNN-based	0.2957	0.2520	0.2082	0.1752	0.1412	0.1183	0.0961	0.0809
GAN-based	0.2943	0.2517	0.2066	0.1655	0.1365	0.1094	0.0966	0.0791
Proposed	**0.2580**	**0.2140**	**0.1821**	**0.1487**	**0.1245**	**0.1031**	**0.0885**	**0.0782**

Table 2: RMSE for various SNR in 16QAM scene.

Methods	-8	-6	-4	-2	0	2	4	6
DAE-based	0.2960	0.2430	0.2000	0.1659	0.1395	0.1195	0.1047	0.0940
CNN-based	0.2957	0.2430	0.2004	0.1665	0.1402	0.1205	0.1057	0.0953
GAN-based	0.2893	0.2383	0.1972	0.1648	0.1399	0.1212	0.1076	0.0980
Proposed	**0.2393**	**0.1985**	**0.1662**	**0.1415**	**0.1229**	**0.1093**	**0.0996**	**0.0929**

set to different amplitude and carrier frequency. For 16QAM modulation signal, the same experiment is carried out to prove the universality of the proposed model. The experimental results are presented in Figure 8. Obviously, the proposed model can still achieve the ideal enhancement effect. It indicates that the proposed model can adapt to various changes in the characteristics of the original signal.

For the case that the clean signal is overlapped by noise and other types of interference signals with the same or similar carrier frequency, the RMSE of the enhanced signal is calculated, the lower the better. Table 1 lists the experimental results for specific SNR and interference type in 16QAM scene. It can be seen that RMSE is significantly reduced by the proposed model. It verifies that the proposed model can not only effectively eliminate the noise, but also moderately reduce the interference with the same frequency.

The enhancement performance of the proposed model for various SNR and unknown interference is evaluated in the last part of the experiment. Specifically, the clean signal in the training set is overlapped by noise with a specific SNR and interference with a specific type. But the SNR range and interference type of noisy signals in the test set are quite different from those in the training set. Table 2 shows the enhancement performance in 16QAM scene. The training set contains noisy signals whose SNR is only 0 dB. For other conditions, noise and interference can still be reduced, which reflects the strong robustness of the proposed model.

The analysis of the above experimental results indicates that the proposed model has better enhancement performance among the competitive methods.

5. Conclusion

Signal enhancement can be embedded into practical applications in the field of wireless communications as a preprocessing module. Traditional enhancement methods usually have some disadvantages, such as the lack of universality for noise and interference and lack of adaptive learning ability for signal features. When the external environment changes, they are difficult to distinguish between the signal and the noise, resulting in the decline of the enhancement effect. In this paper, an end-to-end communication signal enhancement model is proposed to solve the above problems. In the framework of generative adversarial network, the model adopts the encoding-decoding structure based on convolutional layer. It aims to rapidly eliminate noise and interference in the signal. Moreover, the improvement process of the objective function is analyzed, the design structure of the model is provided, and the feasibility of the model is verified by a large number of experiments. The experimental results confirm that the proposed model is more effective for communication signal enhancement than other deep learning-based methods.

Data Availability

The simulated dataset used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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